Youla-Kucera Based Online Closed-Loop Identification For Longitudinal Vehicle Dynamics

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***Abstract*—This paper deals with the identification of longitudinal dynamics of a cycab for subsequent control performance's improvement. Low-speed vehicle dynamic is used as physical model which non-linear behavior is highly complex to properly identify. Among several identification techniques, closed-loop identification gives better performance in a model-based control design. Here, the Hansen scheme is used to transform a closed-loop identification problem in an open-loop-like. The algorihtm is tested in a string of two cycabs equipped with a proportional-derivative-based cooperative adaptive cruise controller, showing how the resulting model is improved in comparison with an open-loop identification algorithm–ARX model.**

***Index Terms*—Closed-Loop system identification, longitudinal vehicle dynamics, linear-parameter-varying system, Youla-Kucera parametrization.**

I. Introduction

Intelligent vehicles field is rapidly growing worldwide [1]. Autonomous cars promise to save time, improve traffic flow, reduce accidents, death and injuries, and make travels accessible and easier to everyone. Despite several demonstrations in recent years, there are still remaining challenges on the road to get fully autonomous vehicles. Manufacturers and academia focus in partially automated vehicles for aiding the driver. Antilock braking systems (ABS), emergency braking, lane changing systems, yaw stability control or adaptive cruise control (ACC) are some examples of already commercial applications. The design of each assistance system involves the specification of a model of vehicle dynamics and its use in the design of the corresponding control to satisfy good performance in different operation points.

Friction force between tire and road is the main reason why vehicle moves [2]. It converts the motor torque to longitudinal force. The conversion depends on powertrain system, engine, aerodynamics resistance, tire/road surface conditions, tire pressure among others [3]. The relation between them brings an insight into the understanding of vehicle dynamics. A complete physical model that really reflects the behavior of the vehicle results in a complex, non-linear dynamic model difficult to achieve. It motivates vehicle dynamics identification by using experimental data; the identified model should capture the nonlinearities of the vehicle while being suitable for control design.

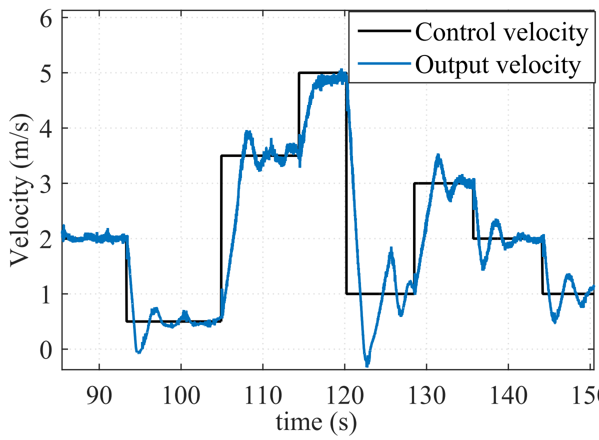

Fig. 1. Nonlinear velocity cycab response.

When it comes to identification methods from online data, linear parameter-varying (LPV) identification [4] offers a systematic way to obtain a non-linear model suitable for non-linear controllers. LPV system is a linear state-space representation whose dynamics vary as function of certain time-varying parameters called scheduling parameters. Two different approaches can be distinguished in LPV modeling: local and global. In local identification, the LPV model is composed by interpolated Linear-Time-Invariant (LTI) models in different operating points; while in global identification, the model changes continously with the scheduling parameter. The latter results in a more accurate model, as it changes with every scheduling parameter's modification [5].

Among open-loop (OL) and closed-loop (CL) identification methods, it is well-known that for model-based control design, CL identification gives better performance [6]. There are several techniques in the literature for LPV identification, but most does not take into account CL operation of the system because its associated difficulties [7] [8] [9]. Using the Hansen scheme proposed in [10], one can transform the CL problem into an OL-like identification problem. The same has been used and extended to LPV systems [11] inside of the Danish research program entitled Plug and Play Process Control [12]. Identification of coupled dynamics in heat distribution systems

[13], and identification of actuators/sensors in the latter [14] were carried out into the project, showing promising model results.

II. Problem formulation

One of the objectives in the development of the Intelligent Transportation Systems (ITS) is to reduce the use of private vehicles in urban areas, by offering new modern and public transportation systems. In order to fulfil this objective, INRIA has developed the cybercar concept (cycab and cybus) as mobile platforms for urban aplications. Cycab has a kinematic structure that differs from that of a car-like: it turns its rear wheels as a linear function of the steering angle of the front wheels [15]. Cycab is commanded through velocity. This velocity is limited to $5m/s$.

The design of different urban applications pass through the correct characterization of the vehicle. When doing cycab characterization (see Fig. 1), a non-linear longitudinal behavior is detected with different time responses and damping factors depending on the control velocity v_c. A non-linear model suitable for non-linear control is needed to satisfy good performance in different operation points. LPV identification fits the needs.

The longitudinal model of cycab G_β can be represented as a minimal state space representation of a LPV system:

$$G_\beta = \left[\begin{array}{c|c} A_\beta & B_\beta \\ \hline C_\beta & D_\beta \end{array}\right] \tag{1}$$

where β is the scheduling parameter, which corresponds to the control velocity v_c.

This system could be stabilized by any appropriate LPV controller K_β, also represented in state-space as:

$$K_\beta = \left[\begin{array}{c|c} A^k_\beta & B^k_\beta \\ \hline C^k_\beta & D^k_\beta \end{array}\right] \tag{2}$$

Here, the global LPV CL identification algorithm provided by the dual Youla-Kucera (YK) parameterization (so-called Hansen scheme) is implemented for identification of longitudinal cycab dynamics. The same is compared with a well-known OL identification algorithm–auto regressive model with external inputs (ARX) [16]. Then, the performance of the algorithm is tested.

The rest of the paper is structured as follows. Section III introduces the mathematical basis used for OL-like identification of a general LPV system. How this theory is applied to CL cycab dynamics identification is presented in Section IV. Comparison results between CL and OL algorithms are obtained both in simulation and experimental environments. Finally, some concluding remarks are given in Section V.

III. OL-like identification of LPV systems

This section introduces the mathematical basis in which Hansen scheme relies on for global LPV CL identification. As already mentioned, Hansen scheme allows OL-like identification through the dual YK parameterization (see [17]). This parameterization is based on the doubly coprime factorization described in [18].

A. LPV doubly coprime factorization

Any controller and model set that satisfies both Eqs. (1) and (2) for any change in the scheduling parameter β, can be rewritten as double coprime factors according to [19]. These coprime factorizations should be such that G_β and K_β are:

$$\begin{aligned} G_\beta &= N_\beta M_\beta^{-1} = \tilde{M_\beta}^{-1}\tilde{N_\beta} \\ K_\beta &= U_\beta V_\beta^{-1} = \tilde{V_\beta}^{-1}\tilde{U_\beta} \end{aligned} \tag{3}$$

These right and left coprime factorizations should be stable and satisfy the double Bézout's identity [18]:

$$\begin{aligned} &\begin{bmatrix} \tilde{V}_\beta & -\tilde{U}_\beta \\ -\tilde{N}_\beta & \tilde{M}_\beta \end{bmatrix} \begin{bmatrix} M_\beta & U_\beta \\ N_\beta & V_\beta \end{bmatrix} = \\ &= \begin{bmatrix} M_\beta & U_\beta \\ N_\beta & V_\beta \end{bmatrix} \begin{bmatrix} \tilde{V}_\beta & -\tilde{U}_\beta \\ -\tilde{N}_\beta & \tilde{M}_\beta \end{bmatrix} = \begin{bmatrix} I & 0 \\ 0 & I \end{bmatrix} \end{aligned} \tag{4}$$

According to [19], coprime factorization to any stabilizing controller in state space can be obtained if Theorem 1 is satisfied.

Theorem 1: *Consider a LPV plant in state space representation as $G_\beta = C_\beta(sI - A_\beta)^{-1}B_\beta$ with $A_\beta, B_\beta, C_\beta$ stabilizable and detectable and a stabilizing controller $K_\beta = C^k_\beta(sI - A^k_\beta)^{-1}B^k_\beta + D^k_\beta$. F^k_β and F^k_β should be chosen such that $A_\beta + B_\beta F_\beta$ and $A^k_\beta + B^k_\beta F^k_\beta \in \mathbb{R}H^{pxm}_\infty$. Then the matrices given by*

$$\begin{bmatrix} M_\beta & U_\beta \\ N_\beta & V_\beta \end{bmatrix} = \left[\begin{array}{cc|cc} A_\beta + B_\beta F_\beta & 0 & -B_\beta & 0 \\ 0 & A^k_\beta + B^k_\beta F^k_\beta & 0 & B^k_\beta \\ \hline -F_\beta & C^k_\beta + D^k_\beta F^k_\beta & I & D^k_\beta \\ -C_\beta & F^k_\beta & 0 & I \end{array}\right] \tag{5}$$

$$\begin{bmatrix} \tilde{V}_\beta & -\tilde{U}_\beta \\ -\tilde{N}_\beta & \tilde{M}_\beta \end{bmatrix} = \left[\begin{array}{cc|cc} A_\beta + B_\beta D^k_\beta C_\beta & B_\beta C^k_\beta & -B_\beta & B_\beta D^k_\beta \\ B^k_\beta C_\beta & A^k_\beta & 0 & B^k_\beta \\ \hline F_\beta - D^k_\beta C_\beta & -C^k_\beta & I & -D^k_\beta \\ C_\beta & -F^k_\beta & 0 & I \end{array}\right] \tag{6}$$

satisfy (3) and (4).

B. Hansen scheme for LPV systems

Dual YK parameterization can be used to recast the CL identification into a OL-like problem. The original method in [10] for LTI systems is extended for LPV systems in [11]. This method is used here once double coprime factorization of the controller/model set is obtained. Thus, all the models stabilized by a controller K_β are represented by:

$$G_\beta = (N_\beta + V_\beta S_\beta)(M_\beta + U_\beta S_\beta)^{-1} \tag{7}$$

From the general description of any model stabilized by K_β in Eq. (7), it is possible to identify new dynamics from an initial model G_β^0 to another one G_β^1 just by obtaining the dual YK parameter S_β. Then the set of all plants stabilized by K_β can be represented by the scheme in Fig. 2. Here, $n' = (\tilde{M}_\beta + \tilde{S}_\beta \tilde{U}_\beta)n_y$ is the measurement noise relocated to affect the output of S_β; and r_1 and r_2 are external excitation signals. From Fig. 2 and Bezout's identity in (4) the following expressions yields:

$$\zeta = \tilde{U}_\beta r_1 + \tilde{V}_\beta r_2 \tag{8}$$

$$z = \tilde{M}_\beta y - \tilde{N}_\beta u \tag{9}$$

Even when control signal u and output y are measured in CL, the identification of S_β is OL-like by using filtered signals ζ and z.

OL identification algorithms like ARX [16] or PBSIDopt [20] can be used for obtaining S_β. By identifying S_β in OL, advantages of CL identification are preserved with a simpler method. The CL equivalent model results:

$$G_\beta^1 = (N_\beta^0 + V_\beta^0 S_\beta)(M_\beta^0 + U_\beta^0 S_\beta)^{-1} \tag{10}$$

IV. Longitudinal dynamics identification

In this section, the described CL LPV identification is applied to the longitudinal dynamics model of the experimental platform already described in Section II. The vehicle is controlled in CL to compare OL and CL identification algorithms.

Here, the controller K (see Fig. 3) is a PD-based cooperative adaptive cruise controller (CACC) as the one in [21]. Its aim is to reduce the response time to different speed changes by using the communication link with its preceding vehicle. Thus, intervehicle distance can be reduced, improving highway capacity. A scheme of the vehicle with the controller in place is shown in Fig. 3; where i is the vehicle index; s_d is a constant distance between consecutive vehicles at standstill; h_d is the constant head time, v_i is the vehicle velocity, d_r is the distance between vehicles obtained by laser, and F a feedforward filter depending on the communication link with the preceding vehicle. Notice how the resulting control signal u will be equivalent to the commanded velocity v_c, while the output y corresponds to the ego-vehicle velocity v_i. The controller K has been designed for a point of operation which is not necessarily the same in all operating points. A better performance could be achieved by designing a LPV controller in terms of the scheduling parameter v_c. The design should be done according to the identified model.

First, an OL LPV model of the vehicle is obtained by using v_c and v_i directly in the ARX model (see [16]). Its basis is equivalent to the following equation:

$$y_{k+1} = Z\theta_k + v_k \tag{11}$$

where y is the output vector, Z the matrix with old inputs and output values, θ_k the model parameters and v_k white noise.

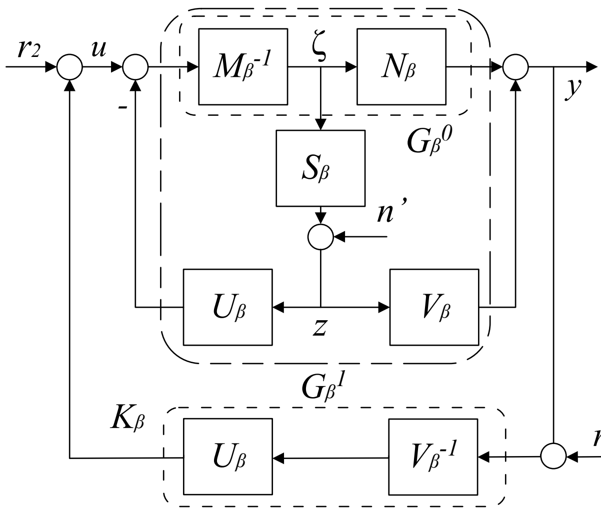

Fig. 2. Hansen scheme for CL identification.

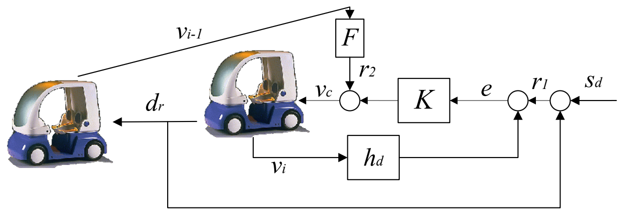

Fig. 3. CACC control structure.

θ_k is found by minimizing the least squared prediction error between real and estimated output.

Then, a CL LPV identification is carried out applying the Hansen scheme presented in Section III. Note that the output of block F (see Fig. 3) and the desired distance relative coming from $s_d + h_d v_i$ serve as external excitation signals r_1 and r_2 in the CL identification. Instead of using v_c and v_i directly in the ARX model, filtered signals ζ and z are employed to get the dual YK parameter S_β. Once S_β is known, the CL vehicle model is updated by using Eq. (10).

In order to evaluate the performance between both algorithms, the metric called Vinnicombe ν-gap in [22] is used. ν-gap goes from 0 to 1 and expresses the difference between two models in reference to similarity in its CL operation. The closer its value to 0, the better the performance. It is been only defined for linear time invariant (LTI) system; its use into LPV systems cames with the definition of a set of LTI systems that composes the LPV model. The ν-gap metric is used during the simulation step with two different LTI models of the cycab. Experimental results regarding real, OL estimated and CL estimated outputs are provided to support the simulation results.

A. Simulation results

As mentioned aboved, two different LTI models are considered for identification comparison. An initial LTI model G_0 of the cycab was obtained when the control velocity changes from $2m/s$ to $4m/s$, resulting in the model shown

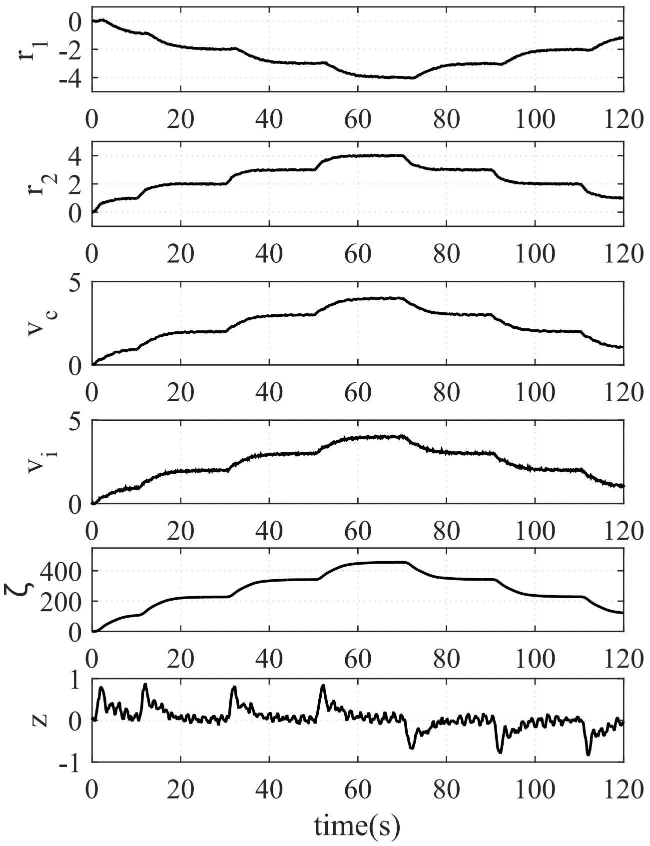

Fig. 4. Signals for identification. Simulation results.

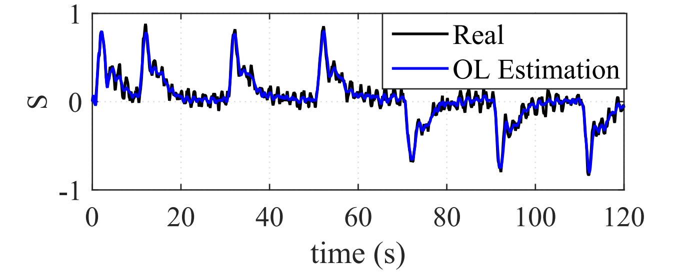

Fig. 5. OL identification of dual Youla-Kucera parameter S. Simulation results.

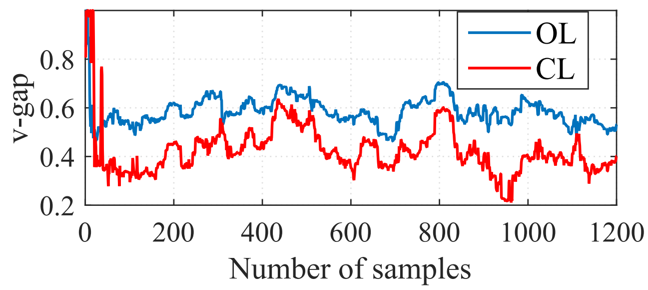

Fig. 6. CL/OL comparison through v-gap metric.

in the Eq. (12). The PD-based CACC controller K is designed under consideration of this LTI model. Controller parameters are found in the Table I. A different LTI model G_1 is also considered, corresponding to the braking phase between $3m/s$ and $1m/s$ (see Eq. (13)). The model G_1 is used together with the controller K. White noise with a signal-noise-ratio (SNR) of $42.42dB$ is added to the output. The modification from G_0 to G_1 emulates the case in which an erroneus model has been identified, being the real one G_1. As the real model is known, ν-gap metric comparison results reliable among OL and CL identified models.

$$G_0 = \left[\begin{array}{c|c} A_0 & B_0 \\ \hline C_0 & D_0 \end{array}\right] = \left[\begin{array}{cc|c} 1.856 & -0.867 & 0.125 \\ 1 & 0 & 0 \\ \hline 0.0818 & 0.00282 & 0.0024 \end{array}\right] \quad (12)$$

$$G_1 = \left[\begin{array}{c|c} A_1 & B_1 \\ \hline C_1 & D_1 \end{array}\right] = \left[\begin{array}{cc|c} 1.787 & -0.846 & 0.25 \\ 1 & 0 & 0 \\ \hline 0.227 & 0.00918 & 0.015 \end{array}\right] \quad (13)$$

TABLE I
CACC PARAMETERS.

Controller parameters	Values
Proportional term k_p	0.5
Derivative term k_d	0.15
Head time h_d	$1s$
Standstill distance s_d	$5m$

An OL identification has been carried out for obtaining the model G_1. Signals v_c and v_i shown in Fig. 4 are used into an ARX model of third order, with one sample delay. The identification is performed using a sliding window approach of 400 samples with a sample time of $0.1s$. The resulting model is compared with G_1 by calculating the corresponding ν-gap.

The proposed identification system computes ζ and z by using Eqs. (8) and (9) with signals r_1, r_2, v_c and v_i in Fig. 4. Notice that these signals are now input and output of the same ARX model. Same order and delay are chosen, so advantages of CL identification can be studied under same conditions. Results of the OL identification of the dual YK parameter S is provided in Fig. 5. The identified S is used in Eq. (10), for obtaining the CL model of the vehicle. The identified model is compared with G_1 through the ν-gap metric.

ν-gap results from OL and CL identification are compared in Fig. 6. A better model is obtained when using ARX model together with the Hansen scheme. Under same conditions, ν-gap results closer to zero. CL nature of the data affects the ARX model, and the Hansen scheme helps to mitigate these effects; obtaining a model closer to the real one.

B. On-vehicle tests

ARX model, Hansen scheme and CACC controller are implemented as defined in the previous section for a string of two cycabs. Different speeds profile are applied to the leader

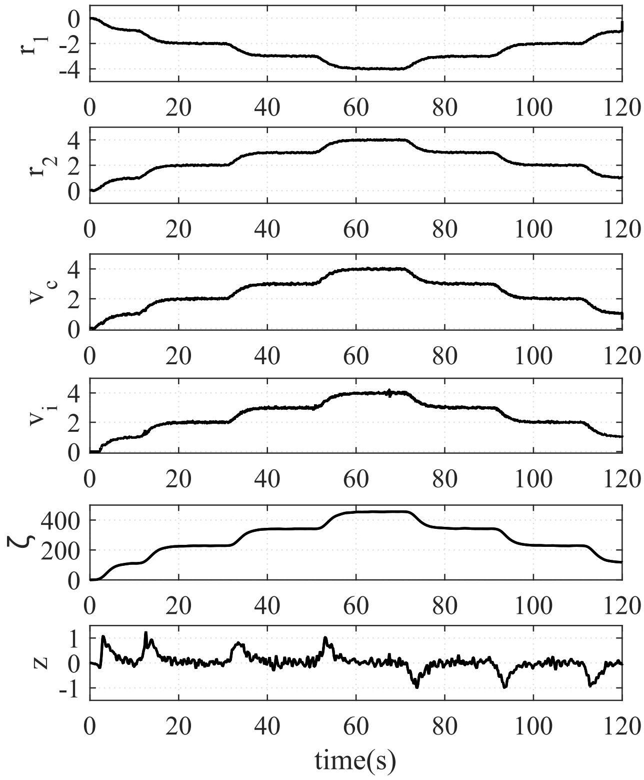

Fig. 7. Signals for identification. Experimental results with soft speed profile.

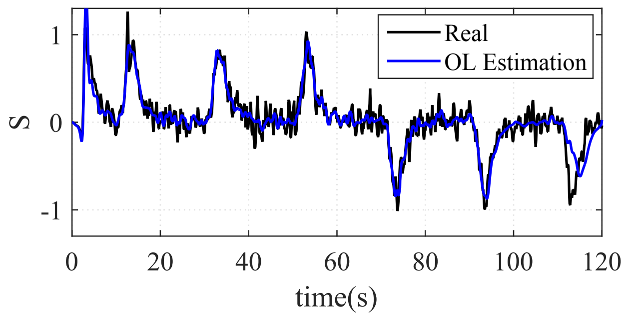

Fig. 8. OL identification of dual Youla-Kucera parameter S. Experimental results with soft speed profile.

of the string, so the algorithm can be tested with slower and faster velocity changes.

The signals from Fig. 7 corresponds to the slower velocity changes case. An OL identification through ARX model is carried out with v_c and v_i; while the same is also used with ζ ans z, for the OL identification of S. Its goodness is proved through results in Fig. 8, where real and identified output of S are compared. Identified S and coprime factors from K and G_0 are used in Eq. (10) to get the CL model of a cycab with a CACC controller. As a priori knowledge of the real model is missing, ν-gap metric is not employed. Instead, estimated output from the model obtained by Eq. (10), OL model and real output are compared in Fig. 9.

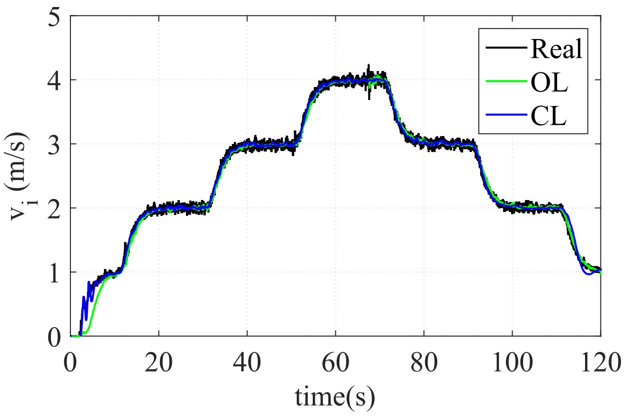

Fig. 9. CL/OL comparison through estimated output. Experimental results with soft speed profile.

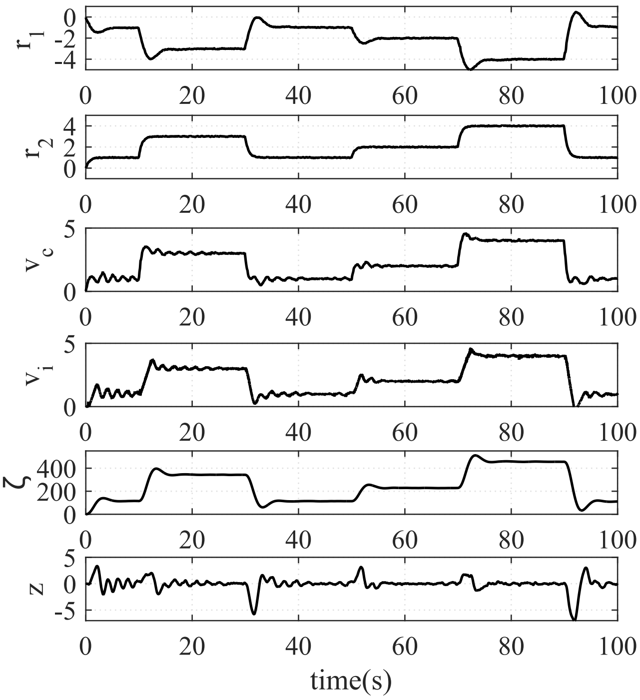

Fig. 10. Signals for identification. Experimental results with abrupt speed profile.

On the other hand, Fig. 10 shows the signals used in the identification for the faster velocity changes case. The procces is exactly the same than in previous cases. It is important to note that goodness of the OL identification for S in Fig. 11 is poorer than in the case of Fig. 8, fact related to the faster signal changes. Even with that, the CL identified model provided by the Hansen scheme is able to follow non-linearities, while the direct ARX model is not. Comparison of identified outputs is shown in Fig. 12. Differences between OL and CL algorithm are visible when faster changes are carried out; demonstrating the good performance of the algorithm previously tested in

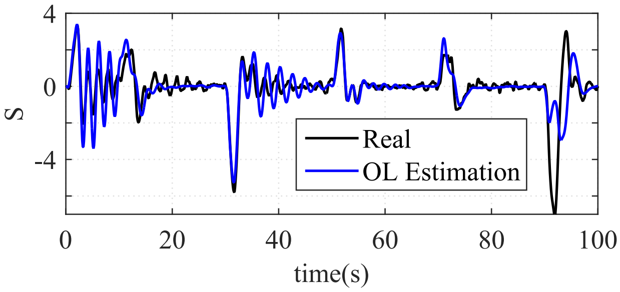

Fig. 11. OL identification of dual Youla-Kucera parameter S. Experimental results with abrupt speed profile.

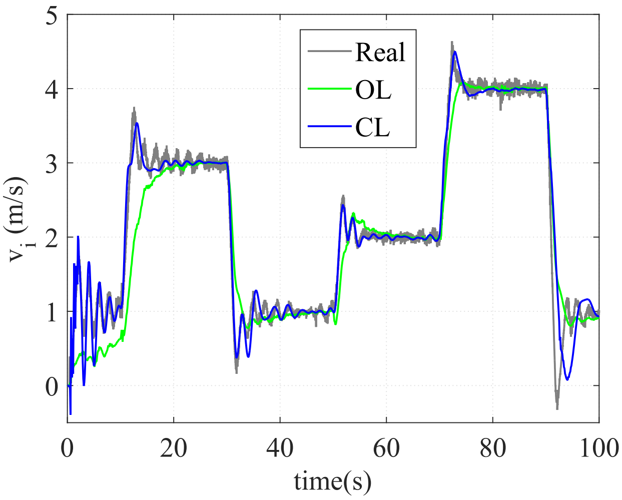

Fig. 12. CL/OL comparison through estimated output. Experimental results with abrupt speed profile.

simulation.

In the latter case, the importance of modeling for controller design is noticeable. The peformance of the controller is quite oscillating, except for the velocity change from $2m/s$ to $4m/s$, which coincides with the identified model G_0 used for the design of K. A LPV controller could provide a better performance in all system operation conditions.

V. Conclusion

In this paper, Hansen scheme is used for CL identification of longitudinal dynamics of a cycab. The good performance of the algorithm is tested when connected to a PD-based CACC controller. The CL identification provided by the Hansen scheme is based in the OL identification of the dual YK parameter S. Thus, the same OL algorithm–ARX model– is used for performance comparison of CL and OL identifications. Simulation and experimental results are conducted to validate the proposed identification algorithm. Results show the feasiblity of the proposed scheme, improving ARX model identification. Future work will be focused on controller tuning depending on the identification to yield better overall system performance.

Acknowledgments

Authors express their gratitude to the french project VALET and the RITS Team for its support in the development of this work.

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